

Fertilizers Recommendation System For Disease Prediction In Tree Leaf

R. Neela, P. Nithya

Abstract: Agriculture is the main aspect of country development. Many people lead their life from agriculture field, which gives fully related to agricultural products. Plant disease, especially on leaves, is one of the major factors of reductions in both quality and quantity of the food crops. In agricultural aspects, if the plant is affected by leaf disease then it reduces the growth of the agricultural level. Finding the leaf disease is an important role of agriculture preservation. After pre-processing using a median filter, segmentation is done by Guided Active Contour method and finally, the leaf disease is identified by using Support Vector Machine. The disease-based similarity measure is used for fertilizer recommendation.

Keywords: Disease Prediction, Graph Cut Algorithm, Guided Active Contour method, Leaf segmentation, Leaf Feature Identification.

1. INTRODUCTION

Detection and recognition of plant diseases using machine learning are very efficient in providing symptoms of identifying diseases at its earliest. Plant pathologists can analyze the digital images using digital image processing for diagnosis of plant diseases. Application of computer vision and image processing strategies simply assist farmers in all of the regions of agriculture. Generally, the plant diseases are caused by the abnormal physiological functionalities of plants. Therefore, the characteristic symptoms are generated based on the differentiation between normal physiological functionalities and abnormal physiological functionalities of the plants. Mostly, the plant leaf diseases are caused by Pathogens which are positioned on the stems of the plants. These different symptoms and diseases of leaves are predicted by different methods in image processing. These different methods include different fundamental processes like segmentation, feature extraction and classification and so on. Mostly, the prediction and diagnosis of leaf diseases are depending on the segmentation such as segmenting the healthy tissues from diseased tissues of leaves.

2 MATERIAL AND METHODS

A digital camera or similar devices are used to take images of different types, and then those are used to identify the affected area in leaves. Then different types of image-processing techniques are applied to them, the process those images, to get different and useful features needed for the purpose of analyzing later-Plant leaf disease identification is especially needed to predict both the quality and quantity of the First segmentation step primarily based on a mild polygonal leaf model is first achieved and later used to guide the evolution of an energetic contour. Combining global shape descriptors given by the polygonal model with local curvature-

based features, the leaves are then classified overleaf datasets. In this research work introduce a method designed to deal with the obstacles raised by such complex images, for simple and plant leaves. A first segmentation step based on graph-cut approach is first performed and later used to guide the evolution of leaf boundaries, and implement classification algorithm to classify the diseases and recommend the fertilizers to affected leaves as shown in Figure 1.

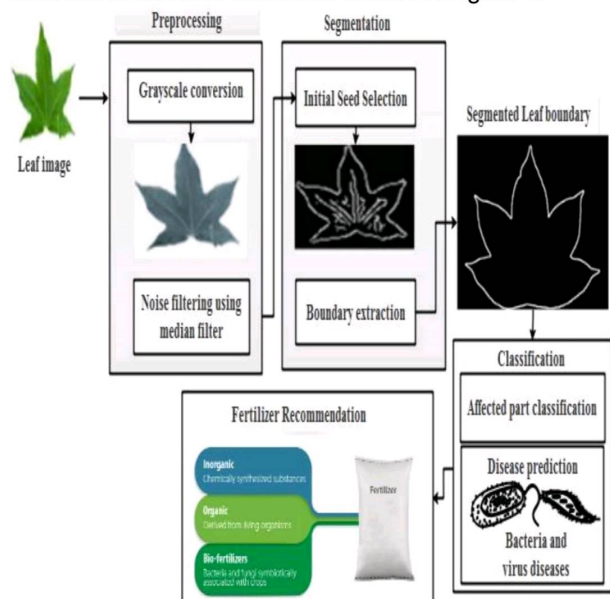


Figure.1 Proposed Architecture

2.1 Image Classification Steps :

The proposed image classification technique is divided into the following steps:

2.1.1 Image acquisition:

To get the image of a leaf so that evaluation in the direction of a class can be accomplished.

2.1.2 Preprocessing:

The purpose of image preprocessing is improving image statistics so that undesired distortions are suppressed and image capabilities which are probably relevant for similar processing are emphasized. The preprocessing receives an image as input and generates an output image as a grayscale, an invert and a smoothed one.

* R. Neela is currently working as an Assistant Professor of Computer Science in A.V.C.College (Autonomous), Mannampandal, Mayiladuthurai-609305, Tamil Nadu, India. E-mail: avcneela@gmail.com

* P. Nithya is currently pursuing M.Phil. degree program in Computer Science in A.V.C.College (Autonomous), Mannampandal, Mayiladuthurai-609305, Tamil Nadu, India. E-mail: nithyapandian2019@gmail.com agriculture plants. This technique is adapted to digital image processing; it has been organized in the

2.1.3 Segmentation:

Implements Guided active contour method. Unconstrained active contours applied to the difficult natural images. Dealing with unsatisfying contours, which would try and make their way through every possible grab cut in the border of the leaf. The proposed solution is used the polygonal model obtained after the first step not only as an initial leaf contour but also as a shape prior that will guide its evolution towards the real leaf boundary.

2.1.4 Disease Prediction:

Leaves are affected by bacteria, fungi, virus, and other insects. Support Vector Machine (SVM) algorithm classifies the leaf image as normal or affected. Vectors are constructed based on leaf features such as color, shape, textures. Then hyperplane constructed with conditions to categorize the pre-processed leaves and also implement multiclass classifier, to predict diseases in leaf image with improved accuracy.

2.1.5 Fertilizer Recommendation:

Recommend the fertilizer for affected leaves based on severity level. Fertilizers may be organic or inorganic. Admin can store the fertilizers based on disease categorization with severity levels. The measurements of fertilizers suggested based on disease severity.

2.2. SVM Classification Algorithm:

Support Vector Machine(SVM) SVM is a binary classifier to analyze the data and recognize the pattern for classification. The main goal is to design a hyperplane that classifies all the training vectors in different classes. The objective of SVM is to identify a function F_x which obtain the hyper-plane. Hyperplane separates two classes of data sets. The linear classifier is defined as the optimal separating hyperplane. The data sets can be separated in two ways: linearly separated or nonlinearly separated. The vectors are said to be optimally separated if they are separated without error and the distance between the two closest vector points is maximum. For linear separable data sets, training vectors of a different class of pairs (a_m, b_m) , where $m = 1, 2, 3, 4, \dots, t$
 $a_m \in R^n$ (Reference Vector)
 $b_m \in \{+1, -1\}$

The decision boundary is placed using a maximal margin between the closest points. w is being a vector perpendicular median to the street. a_m be the unknown of to be positioned especially elegance according to the decision boundary, and hyperplane $(w \cdot a) + c = 0$ with c as constant

For classification

$$(w \cdot a_m) + c_0 \geq 1, \forall$$

$$b_m = +ve \text{ samples} \quad (1)$$

$$(w \cdot a_m) + c_0 \leq -1, \forall$$

$$b_m = -ve \text{ samples} \quad (2)$$

where $(w \cdot a_m)$ has a dot product of w and a_m .

The inequalities if added i.e multiplying equations (1) and (2) with $+1, -1$ and b_m .

Suppose b_m such that

$b_m = 1$ for $+ve$ samples

$b_m = -1$ for $-ve$ samples

it results,

$$b_m [(w \cdot a_m) + c_0] \geq 1$$

$$b_m [(w \cdot a_m) + c_0] \geq -1$$

Therefore rearranging the above equations $b_m (w \cdot a_m) + c_0 - 1 \geq 0$ for points into dataset to in the gutter i.e on the decision boundary $b_m (w \cdot a_m) + c_0 - 1 = 0$.

3. RESULTS AND DISCUSSION

To compare the performance of the proposed SVM method with the existing CNN (Convolutional Neural Network) method. Metrics such as True Positive, False Positive, True Negative, False Negative are used. The proposed method is implemented using .NET. The code existing CNN method was written in Python was downloaded from the web [https://github.com/cs-chan/Deep-Plant]. 15 images were captured using a camera for testing purpose is given in Figure 2.

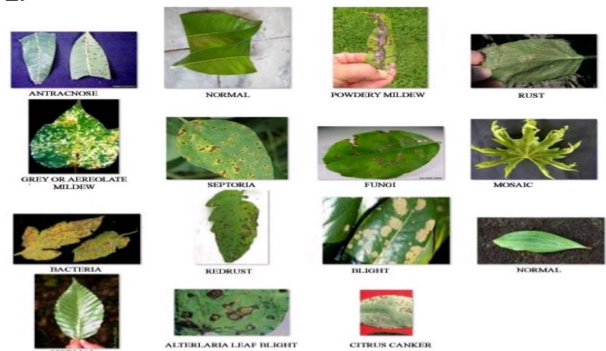


Figure.2 Input Images

Firstly, some secondary metrics such as true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) [18] are calculated as follows,

True Positive: True Positive is an outcome where the model correctly predicts positive class. False Positive: False Positive is an outcome where the model incorrectly predicts positive class. True Negative: True Negative is an outcome where the model correctly predicts negative class. False Negative: False Negative is an outcome where the model incorrectly predicts negative class. The True Positive, False Positive, True Negative, and False Negative value for captured 15 images are shown in table 1. The pictorial representation of this comparison is given in Figure 3.

TABLE 1

COMPARISON OF CNN AND SVM IN TERMS OF TP, FP, TN, AND FN

Methods	TP	FP	TN	FN
Existing [CNN]	6	3	2	4
Proposed [SVM]	8	4	1	2

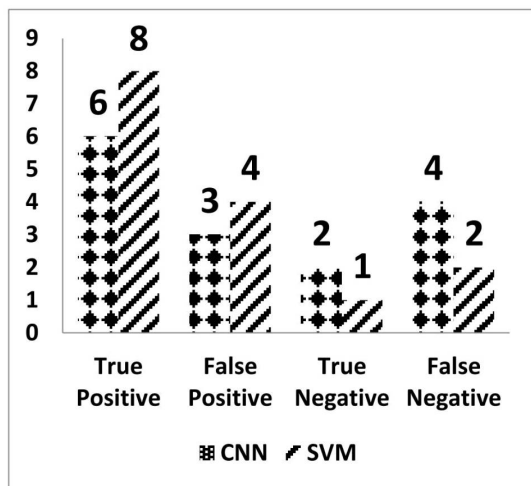


Figure.3 Performance comparison of CNN and SVM in terms of True Positive, False Positive, True Negative and False Negative.

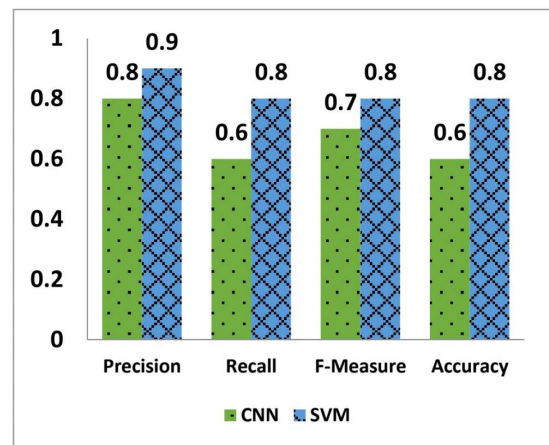


Figure.4 Precision, Recall, F-Measure and Accuracy comparison chart for CNN and SVM

Precision: The proportion of positive identification is actually correct.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Recall: The proportion of actual positives is identified correctly.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

F-Measure: Defined as the weighted harmonic mean of precision and recall.

$$\text{F-Measure} = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN})$$

Accuracy: It refers to the closeness of a measured value to a standard or known value.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{FP} + \text{TP} + \text{FN} + \text{TN})$$

The Precision, Recall, F-Measure and Accuracy for the both CNN and SVM are calculated and given in table 2 the corresponding graph is given in Figure 4.

TABLE 2

PRECISION, RECALL, F-MEASURE AND ACCURACY VALUES OF CNN AND SVM

Classifiers	Pre	Re	F-M	Acc
CNN	0.8	0.6	0.7	0.6
SVM	0.9	0.8	0.8	0.8

4. CONCLUSIONS

The proposed method uses SVM to classify tree leaves, identify the disease and suggest the fertilizer. The proposed method is compared with the existing CNN based leaf disease prediction. The proposed SVM technique gives a better result when compared to existing CNN. For the same set of images, F-Measure for CNN is 0.7 and 0.8 for SVM, the accuracy of identification of leaf disease of CNN is 0.6 and SVM is 0.8.

5. FUTURE SCOPE

This further research is implementing the proposed algorithm with the existing public datasets. Also, various segmentation algorithms can be implemented to improve accuracy. The proposed algorithm can be modified further to identify the disease that affects the various plant organs such as stems and fruits.

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